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COMMENTARY

Can remote sensing of land cover improve species distribution modelling?

Remote sensing has been used as a tool for mapping land cover since sources of data became readily available in the 1970s. Spectral, temporal, and textural differences among satellite images allow users to distinguish among broad classes of vegetation. However, the applicability of remote sensing to classification breaks down at the species level. General categories of vegetation, such as deciduous and coniferous forests, can be separated, provided patches are relatively homogenous, but species with similar growth forms, for example pine and fir, are problematic. Hence, there is a gap between what an ecologist would like from remote sensing – a map of tree species – and what can be delivered – a map of forest types.

Land cover maps derived from remote sensing often are not detailed enough to improve predictions of species distributions based on ecological niche modelling or similar approaches. In addition, land cover classification yields a fairly small number of nominal variables (e.g. deciduous forest, coniferous forest, mixed forest, grassland). By contrast, climatic and topographic data typically have a greater range of continuous values, and are more often used for predicting species distributions (Guisan & Zimmermann, 2000). This is especially true across large regions with grossly similar land cover (for example forests in the Amazon Basin).

Many animal species do not rely on a single species of plant to define their habitat or the quality of that habitat; birds are thought to respond to vegetation structure in addition to composition, particularly at coarse scales (e.g. MacArthur *et al.*, 1966; Rotenberry, 1985) and in temperate regions. The structural complexity of vegetation and the relative proportion of cover in the understorey, shrub layer, and canopy encompass a suite of characteristics (for example nest predation risk, abundance and diversity of food resources, microclimate) that strongly affect the quality of habitat for nesting and relative nest success (Wiens, 1989). Some of these integrated landscape characteristics can be measured with remote sensing.

Derived products, such as land cover maps, are only one element of a wealth of remote sensing data. Could remote sensing provide information on other landscape characteristics that affect the distribution of animal species? For example, even if vegetation composition is unknown, could variables such as overall greenness and seasonality be associated with occurrence patterns?

Buermann *et al.* (2008) explored the latter questions for several species of birds, mammals, and trees in the Amazon Basin. They found that distribution models that included topographic, climatic, and remote sensing-derived vegetation variables often were more accurate than models that included only topographic and climatic variables. Rather than using a land cover map to model species distribution, Buermann *et al.* used indices of vegetation and radar scattering data, both of which provide a much greater range of continuous data values than vegetation classification alone. This approach may lead to improved models of species distributions if appropriate remote sensing data are selected as input variables.

The array of global remote sensing data, ranging from surface reflectance to thermal emissivity, and of derived products, ranging from leaf area index (LAI) to tree cover, can be overwhelming. Additional remote sensing data sets with the potential for improving distribution models include topographic data from the shuttle radar topography mission (SRTM) and precipitation data from the tropical rainfall measuring mission (TRMM). Here, we focus only on remote sensing data specifically related to vegetation. As for any ecological model, the most appropriate remote sensing data for models of species distributions will vary taxonomically and geographically, but some general information can guide the selection of vegetation variables derived from remote sensing.

The normalized difference vegetation index (NDVI), a proxy for photosynthetic activity, is commonly used for assessing landscape characteristics. It can be derived from readily available data [for example Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS)]. Other indices, such as LAI, the enhanced vegetation index (EVI), and the fraction of photosynthetically active radiation (fPAR), also relate to overall greenness and productivity. Mean annual NDVI has been shown to correlate with the species richness of birds in a desert ecosystem (Seto *et al.*, 2004), and may relate to the distributions of individual species (B. Dickson *et al.*, unpublished data).

Vegetation phenology, derived from NDVI or other vegetation indices, may also provide insight into habitat quality. For example, the starting date of the growing season derived from time series of NDVI has been used to predict malarial outbreaks in Africa, implying a link between mosquito life cycles and changes in NDVI (Rogers *et al.*, 2002). In another study, Osborne *et al.* (2001) showed that the timing and amplitude of NDVI-derived land surface phenology in Spain differed among sites at which Great Bustards (*Otis tarda* L.) were present or absent, suggesting that ecosystem phenology helps to define the species' habitat. Time series phenological markers that may prove useful for species distribution modelling include start date and length of the growing season, and date of maximum greenness as well as the more commonly used mean, maximum, and amplitude of NDVI.

Another influence on species distributions that cannot be estimated with climate variables alone is land use. For example, deforestation reduces the extent and quality of habitat for many species. Data on deforestation can be derived from remote sensing and included in a distribution model. Other GIS-based land-use layers (for example roads) can also be used to model habitat quality, but in areas where human activity is

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poorly documented, remote sensing has particular value.

Active radar or lidar measurements provide further potential for measuring structural characteristics of vegetation. Currently, lidar data, which measure canopy and understorey heights based on the strength and timing of the return of a long-wavelength laser (Lefsky *et al.*, 2002), are not available globally. However, Buermann *et al.* (2008) showed that radar data from QuikSCAT (a sensor initially designed to measure ocean roughness) provided better models of the distributions of bird species than did LAI data. Radar data are sensitive to moisture content and canopy roughness, which may be more relevant than LAI to Buermann *et al.*'s target species, and they are also more sensitive than vegetation indices to spatial heterogeneity in forests.

A great strength of remote sensing-derived vegetation variables as compared with climatic variables is their wide spatial and temporal coverage. Since 1982, global-scale 8-km resolution NDVI data have been available as monthly products from the advanced very high-resolution radiometer (AVHRR) satellite (Tucker *et al.*, 2005). Since 2000, global-scale 1-km resolution NDVI, EVI, LAI, and fPAR data have been available as bi-weekly products from MODIS. Remote locations hundreds of kilometres from a weather station have been imaged repeatedly. Such coverage will never be possible for climatic variables, which typically are interpolated from weather station data. Climatic variables derived from remote sensing (for example TRMM) are promising, but average climatologies are currently available at coarse resolution only (0.25° for TRMM). In areas with sparse weather stations, remote sensing data on vegetation may even provide a better proxy for climate than climate interpolations.

Because vegetation data may act as a proxy for climate it can be difficult to determine the extent to which species distributions respond to vegetation structure *per se*. For example, an association between the distribution of a given bird and LAI could imply either that habitat quality is directly affected by vegetation productivity or that habitat quality is a function mainly of climate, which affects both birds and vegetation. In this case, remote sensing data may identify patterns, but observational or manipulative field studies may be necessary to understand the underlying mechanisms.

Despite wall-to-wall coverage, remote sensing data are frequently subject to cloud disruption. Many parts of the Earth, particularly the tropics, are extensively cloud-covered, making it difficult to derive average greenness estimates and phenological markers. Active sensors, including radar, penetrate cloud cover more reliably. If cloud contamination is known, remote sensing metrics that reduce cloud impact, such as annual maximum NDVI, can also be used. Furthermore, time series interpolation techniques, such as Gaussian or spline-based curve fits, reduce the impact of clouds (Jonsson & Eklundh, 2002; Bradley *et al.*, 2007), and temporal averaging can minimize cloud error. However, the inclusion of cloud-prone data in a species distribution model may add more noise than signal.

A final challenge lies in the interpretation of remote sensing data. Understanding the ecological importance of vegetation greenness on quality of habitat for a given species is straightforward, but interpreting the influence of, for example, radar scattering on habitat quality is more difficult. Radar data may be related to canopy roughness, moisture level, and biomass, but the link between the remote sensing product and habitat quality is indirect. The trade-off of an improved species distribution model may be reduced ecological meaning.

Remote sensing data on vegetation are intriguing complements to climatic and topographic variables for species distribution modelling. Although land cover classifications derived from remote sensing are of limited use for distribution models, remotely sensed time series for other attributes of vegetation could add another dimension of information. Vegetation structure, productivity and phenology may influence the quality of habitat for some species to the same extent as temperature and precipitation. Creative approaches, inclusive of multiple data sources, can only improve future species distribution modelling efforts.

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